

Continue with
regression

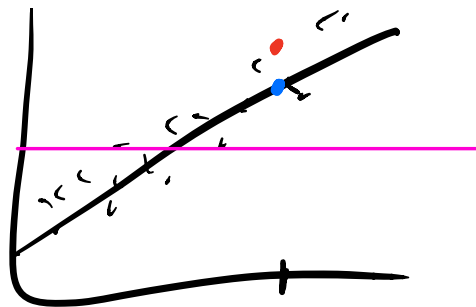
Some data (x, y)

$$\text{lm}(y \sim x)$$

\neq

$$\text{lm}(x \sim y)$$

Errors from predictions



$$\text{rms error} = \text{rms of pred error}$$

$$\text{pred error} = \text{actual} - \text{pred error}$$

If we just guessed the average of y for every x
then $\text{RMS error} = \text{SD}_y$

For regression

$$\text{rms error} = \sqrt{1-r^2} \cdot \text{SD}_y$$

$$\text{since } -1 \leq r \leq 1$$

$$\Rightarrow 0 \leq \sqrt{1-r^2} \leq 1$$

$$\text{if } r=1 \Rightarrow \sqrt{1-r^2}=0$$

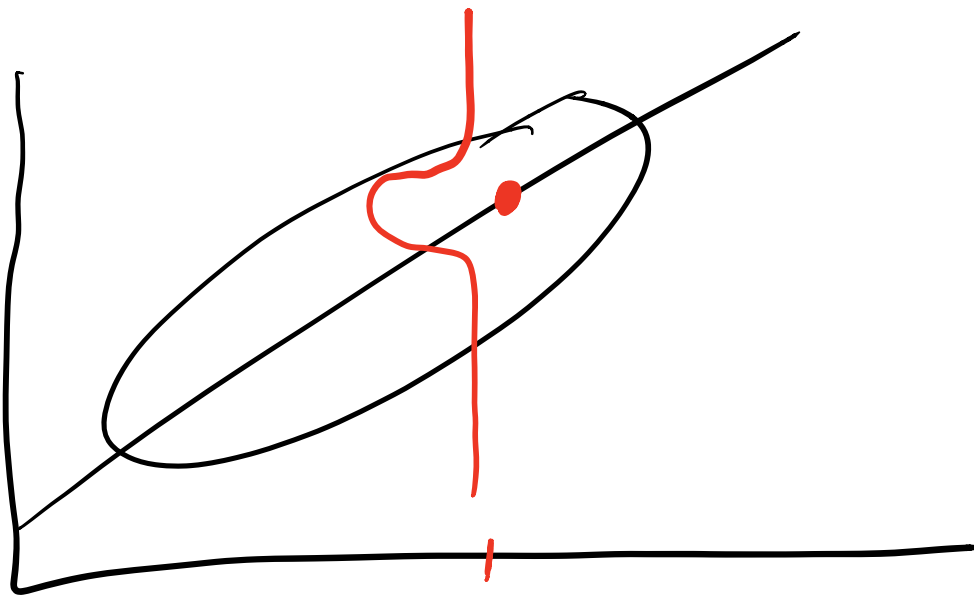
perfectly linear relationship
error = 0

if $r=0 \Rightarrow \sqrt{1-r^2} = 1$

$$\text{RMS reg} = \text{SD}_y$$

no better off than guessing
the avg of y .

The strips of normality



The equation of the line

$$y = mx + b$$

For the lin. regression

$$m = r \cdot \frac{SD_y}{SD_x}$$

$$b = \text{avg}_y - m \cdot \text{avg}_x$$

If you recall last time

$$y_p = \left(\frac{x - \text{avg}_x}{SD_x} \right) \cdot r \cdot SD_y + \text{avg}_y$$

$$= X \cdot r \cdot \frac{SD_y}{SD_x} + \text{avg}_y - \text{avg}_x \cdot r \cdot \frac{SD_y}{SD_x}$$

$$= X \cdot m + \text{avg}_y - \text{avg}_x \cdot m$$

$$= mx + b$$